Final report: From Fly Models to Flight Control
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Michael H. Dickinson, 2006

Abstract

The mobile flying robots of the future will face the daunting challenge of operating autonomously in complex dynamic environments. They will need to employ an array of sensors to meet a set of mission goals that might include long distance navigation, obstacle avoidance, chemical tracking, object identification, and controlled landing. Many animals, such as common flies, have solved most or all of these challenges in a robust and flexible manner that nevertheless uses a hard-wired control architecture. Not only are flying flies amongst the most stable and maneuverable of all animals, but the display a behavioral flexibility that allows them a high rate of success under a variety of different internal and external conditions. A fly simultaneously implements, at a small time-scale, an extremely rapid and stable flight control system while, at larger time-scales, behavioral tactics for finding rare and patchy food sources.

In the research covered in this report, we integrated findings from biology to create a bottom-up model of the visual, mechanical, and aerodynamics systems the fruit fly to investigate the above general questions. Couched in the language of control systems, the model allows us to make detailed predictions about fly behavior under a given set of assumptions. Thus, we can simultaneously investigate, on the one hand, the actual strategies employed by the fly, while, on the other hand we can evaluate the theoretical performance of various algorithms under a variety of conditions impossible to test in real experiments. We have used the model to generate closed-loop flight in a tunnel geometry.

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1.Background

Unmanned aerial vehicles (UAVs) have removed the human pilot from the aircraft, utilizing software that integrates output from a diverse array of sensors to control actuators governing flight, potentially allowing significant autonomy. The tasks involved in controlling an aircraft are difficult and multi-scale. At a low level, the flight actuators must be regulated using appropriate data to produce desired thrust while maintaining stability. At a middle level, changes in airspeed, encounters with turbulence and approaching obstacles must be detected and trigger appropriate reactions. And at a high level, a desired trajectory must be tracked or other mission objectives met. Although operating at different spatial and temporal scales, control at one level is coupled to the others. Sensor data arrives from instruments with different spatial ranges, temporal dynamics, and functions, including imaging devices, gyroscopes, air speed sensors, and chemical detectors. Despite the use of onboard processing to provide some degree of autonomy, the challenge presented by these issues remains daunting. UAVs often require both a human operator to provide higher levels of control and powerful computers capable of performing the remaining tasks. How do we begin to think about a creating a system which solves these problems completely autonomously, which does so despite changing and potentially adverse environmental conditions, and which is capable of doing so without vast computational resources?

Almost all the characteristics necessary for such a completely autonomous flying device may be found within the control systems of a common fly (see Figure 1). Successful strategies for high-level behavior, such as localization of a food source by a fly, require an integration of visual, olfactory, and mechanosensory information into a motor program that simultaneously meets low-level needs (e.g. stable forward flight, obstacle avoidance) and serves higher-level functions (efficient search of a region of interest). The robustness of the tactics used by flies is evident upon consideration of the large range of internal and external perturbations (damaged wings, gusts of wind) and varied environments (a sun-parched desert, an orchard floor, or even a dark kitchen trash can) over which flies live. The apparent simplicity of the fly nervous system may provide insight into the principles by which high level goals are achieved in a robust manner. The nervous system of a fly contains approximately 350,000 neurons, about half of which are dedicated to visual processing. When compared to mammalian systems with many orders of magnitude more neurons, it is apparent that flies have found a reduced yet successful solution. This solution does not require learning or training; flies fly like aces from the moment they emerge from their puparium (a flies 'cocoon'). Much of the seemingly intelligent behavior of flies may result as an emergent behavior arising from the ongoing activity of multiple sensory-motor control rules acting simultaneously and in concert with each other to govern wing movements and ultimately the trajectory through the environment and success at a given task. Experiments involving simulated, artificially evolved agents show that simple artificial neural networks are capable of implementing successful high-level behaviors such as landmark localization using purely instantaneous control of motor output based on visual input. The similarity of such artificially evolved solutions to actual insect behavior in this case indicates that this approach, a simultaneous exploration of simulated and biological agents, may reveal general solutions to the demands of the task rather than reflections of historical constraints.
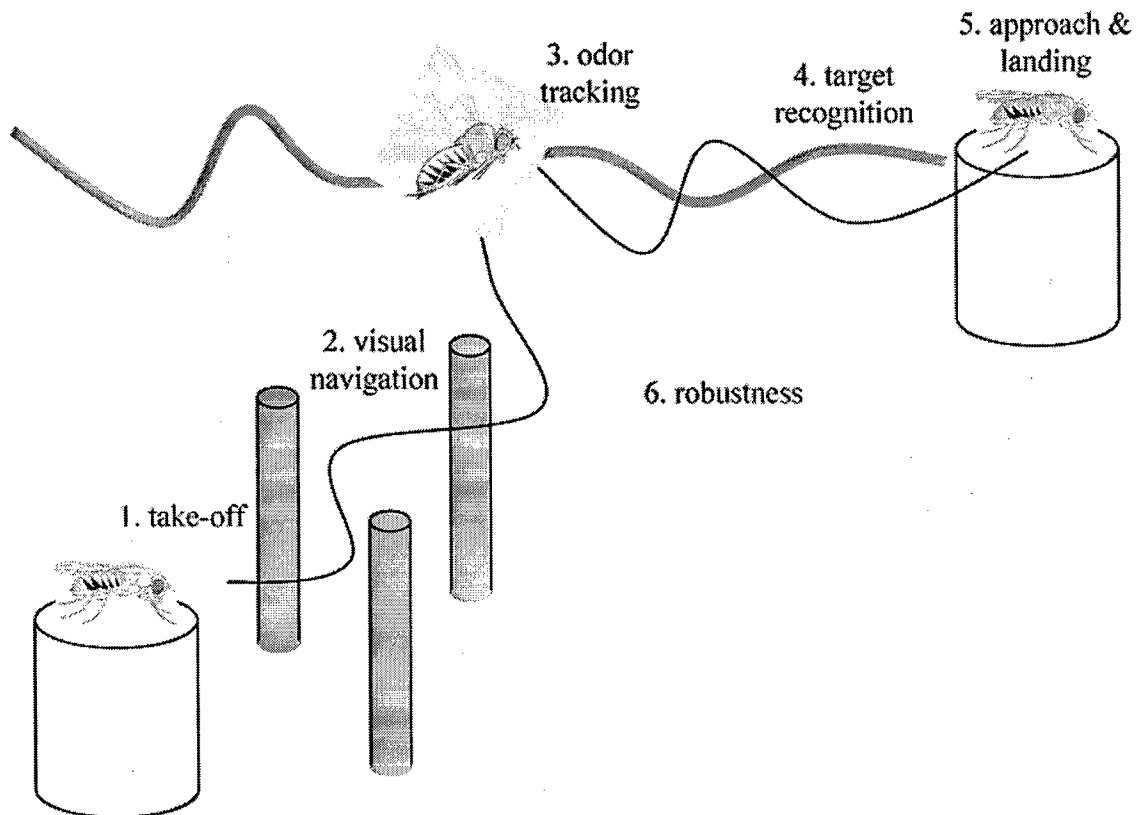
Figure 1. Example of typical higher-order flight control strategy involving (1) flight initiation, (2) visually based navigation and obstacle avoidance, (3) odor tracking and odor source localization, (4) visual/olfactory target recognition, (5) visual and mechanosensory control of approach and landing. Over a large range of internal and environmental conditions, flies perform well, leading to the idea that they exhibit (6) robust behavior.

In the simplest terms, a fly's nervous system acts as a complex processor fusing thousands of channels of sensory information to control a multitude of output degrees of freedom. It does so not only with regard to momentary stability considerations, but also as an ongoing process by which larger-scale strategies are implemented. Flies do not have stabilizing surfaces, so critical in all current aircraft designs. Moreover, flight is stable despite the lack of a steady propulsion system, depending instead on complex, unsteady flows generated by flapping wings. Utilizing such a system of actuation and control, flies locate food sources in unknown and changing environments over long distances. From the perspective of control theory, robotics, and artificial intelligence, the robustness and flaw tolerance of the fly's flight control system and emergent behavioral strategies represent gold standards by which all autonomous systems might be judged. The fact that the neural circuitry creating this behavior resides in a brain the size of a poppy seed raises the bar for any effort attempting to match its performance using even the most sophisticated digital processing hardware. If the principles that engender a fly with such robust agility and such successful behavior organized in a bottom-up fashion could be discovered and formalized for general use, the result would catalyze a revolution in the design, fabrication, and implementation of autonomous systems.

2. Research Performed

Dynamic simulation

A realistic model of the fruit fly's visual-motor flight system was developed within our laboratory (Fig. 2). The simulated fly may be placed in an arbitrary three dimensional environment with realistic visual and kinematic components. This model is capable of autonomous, stabilized flight through a winding tunnel by controlling heading angle through modulation of wing kinematics based on visual control signals (Fig. 3). Adding realistic olfactory and mechanosensory components will be relatively straightforward within the present environment and will allow pursuit of the research objectives, serving as a test bed to explore individual sensory-motor control laws and their interaction to produce higher-level behavior implementing strategies such as odor source localization.

A

B

C

D
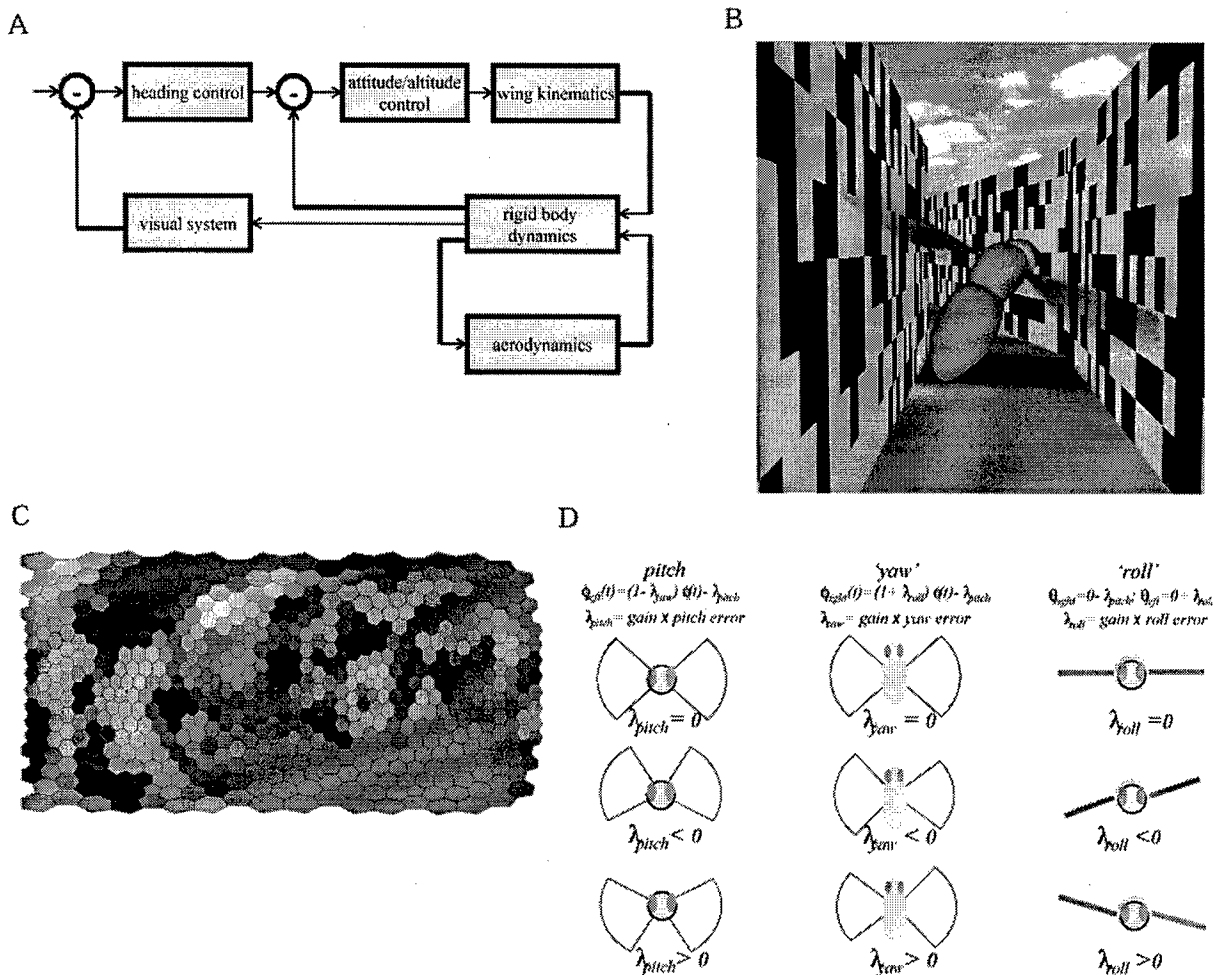
Figure 2: Dynamic flight simulation integrating visual/motor system models with a realistic flight mechanics. (A) Block diagram illustrating the flight controller utilizing visual information for heading control. (B) Rendering of simulated fly navigating a curved tunnel using visually based controller. (C) Photoreceptor outputs. (D) Motor system deformation modes for pitch, roll, and yaw.

The visual system model begins with an environment model within a three dimensional

computer graphics engine designed for real time, realistic visual simulations such as computer games. Simulated photoreceptor inputs are calculated based upon the position and orientation of the simulated fly and optical parameters such as the geometry of the compound eye and the angular acceptance function of each receptor. Photoreceptor outputs are then used to calculate local, elementary motion detector outputs (EMDs) based upon the well known Hassenstein-Reichardt correlator model using physiologically plausible parameter values. EMD outputs are spatially integrated to provide wide-field motion detector responses similar to those found in real flies, which are then used as a control signal for the motor system.
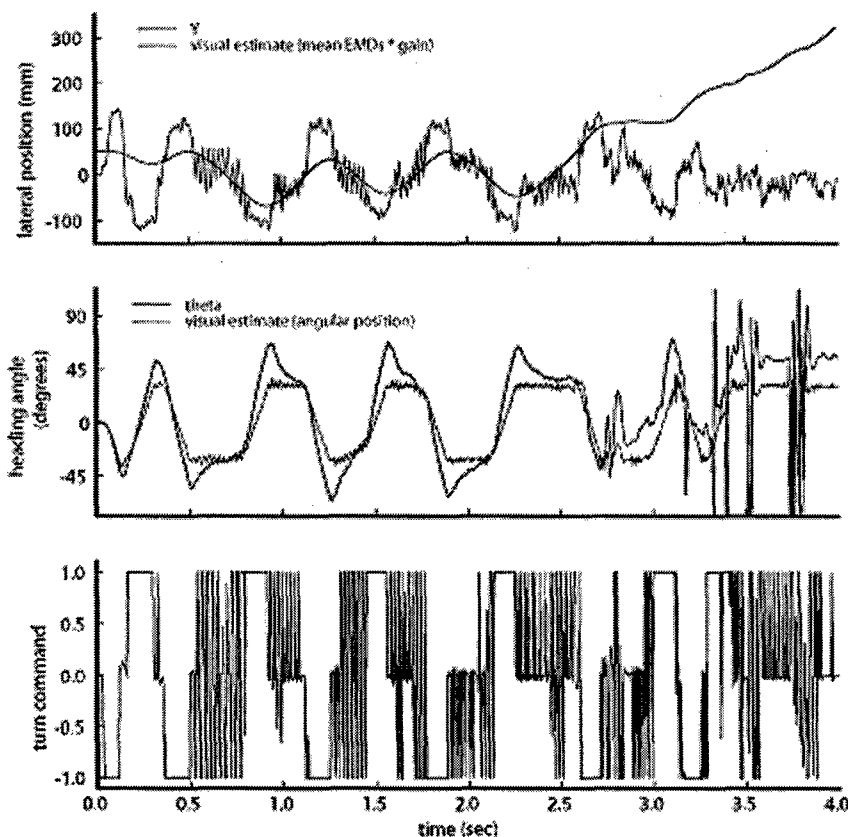
A   B
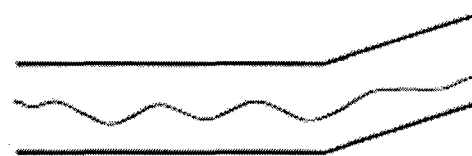
Figure 3: Visually-computed information, derived control signal and behavioral output of dynamic model. (A) Time course of lateral position , heading angle, and controller turn command. (B) Top view showing flight trajectory of simulated fly and tunnel geometry.

The motor system model provides a concise description of the effect that the control muscles have on the wing kinematics of a fly. In the model, the motor system is implemented such that it is not the details of control muscle firing patterns which are important, but rather the motion of the underlying actuators, the wings. Thus, in this context, what is required is a mapping from sensory inputs to actuation; how this is achieved on a neuromuscular level is not of primary interest. The description of the mapping of sensory information to wing motion is simplified by characterizing a finite set of deformation modes of an underlying baseline pattern of wing kinematics. Thus the mapping from sensory input to wing motion is reduced to mapping onto a finite set of real numbers describing magnitude of the underlying deformation modes for a given sensory input.

The flight mechanics model consists of a physics engine designed for simulating the motion of articulated rigid bodies and an aerodynamics model of the forces and moments produced by motion through the atmosphere. In the model a fly is approximated as a system of three articulated rigid bodies. One rigid body is used to represent the fly's body and the other two are used to represent the wings. The rigid bodies are based on polygonal representations generated using calibrated images of a fly's body and wings. The system of rigid bodies representing the fly is connected by ball joints (representing the wing hinges) which are actuated via angular motors. The aerodynamics model is used to estimate the forces and moments generated by the flapping wings as well as the body. A quasi-steady blade element model is used for calculating the forces and moments generated by the wings. This model accounts for forces due to the aerodynamic mechanisms of delayed stall, rotational circulation, and acceleration reaction. Body forces and moments due to linear translation and rotation are estimated using a quasi-steady model with force coefficients derived from experiments in a tow tank using a six-axis sensor and dynamically scaled body model.

Multiple camera fly tracking system and free-flight wind tunnel

To capture the free flight dynamics of flies with sufficient temporal and spatial resolution over a large behavioral volume, we have developed a multiple camera system which allows tracking of freely flying flies (Fig. 4A,B). In addition to its basic role as a data acquisition device, this system operates in real-time (100 or more frames per second, < 30 msec latency), allowing the experimenter to control sensory stimuli based on a fly's position and orientation, allowing manipulation of visual feedback during flight (Fig. 5). Additionally, we have developed a technique for estimating the roll angle of the fly based on the resultant forces extracted from the observed kinematics, a model of aerodynamic drag, and an assumption that fruit flies are unable to generate thrust with a side-directed component. With an estimate of roll angle and experimental fixing of the head stationary relative to the thorax, all six degrees of freedom of the fly's head are known, allowing a detailed reconstruction of the input to fly's visual system (Fig. 4C). This tracking system is used in conjunction with a low velocity wind tunnel, allowing free flight experiments regarding the integration of visual and mechanosensory information resulting from movement relative to both the air and ground (Fig. 5B). Furthermore, odors may be introduced within the tunnel to investigate olfactory influences on motor output and behavior (Fig. 6).
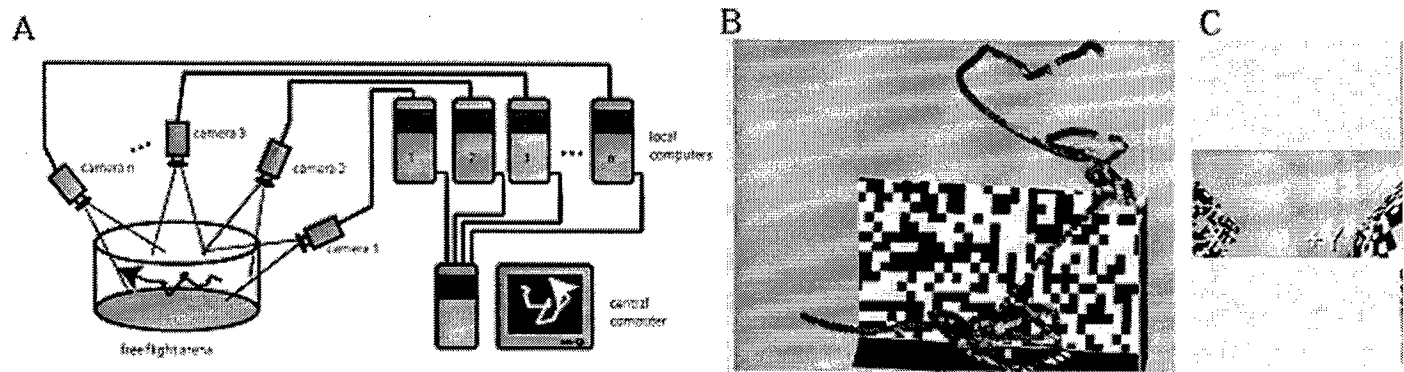
Figure 4. Multiple camera fly tracking system used for three dimensional capture of free flight trajectories. A) Schematic diagram showing use of multiple cameras and computers to compute fly position and orientation with minimal (<30 msec) latency. B) Reconstructed flight trajectory shows a fly approaching an attractive odor source placed within a visually textured arena. C) View reconstructed from the fly's perspective. From this representation, simulated optical and physiological filtering can be applied to produce, for example, realistic visual motion detector outputs.
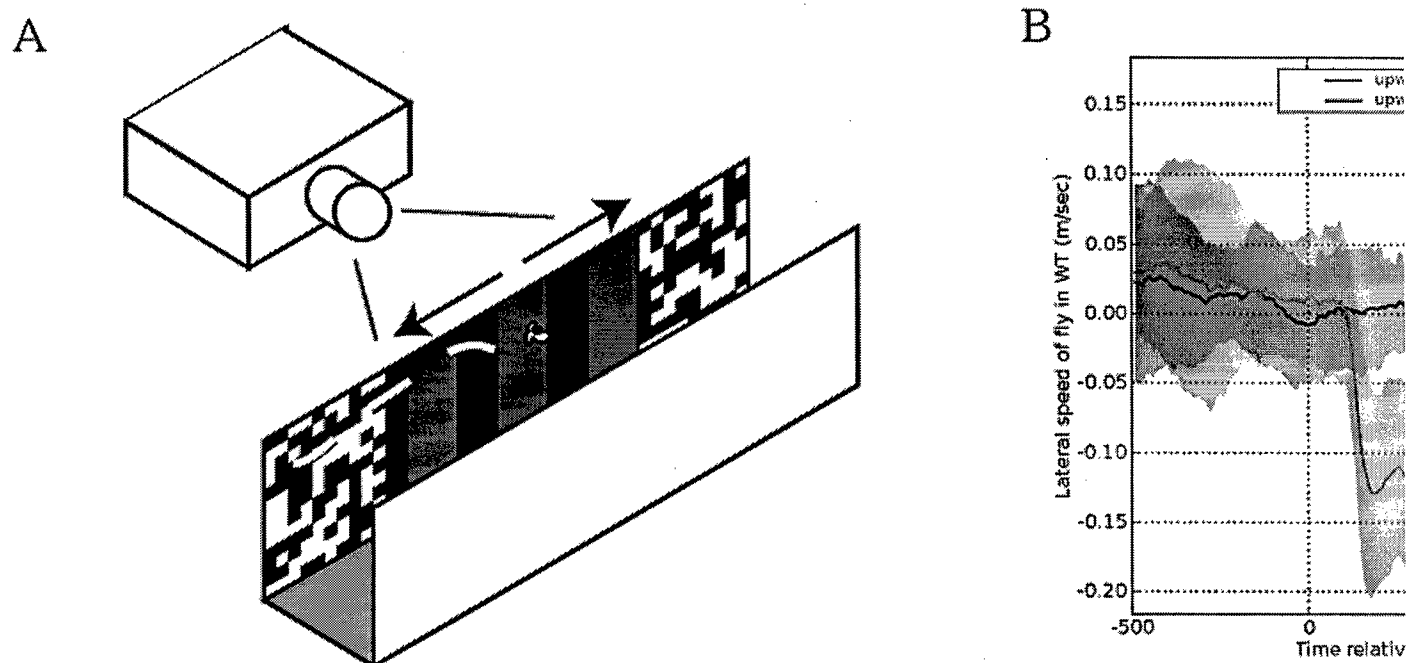
Figure 5: Free flight experiments show that flies move away from visual expansion. A) Experimental apparatus uses a real time signal of fly position to trigger movement of parallel bars away from a focus of expansion. B) Freely flying flies respond to visual expansion by rapidly moving away.
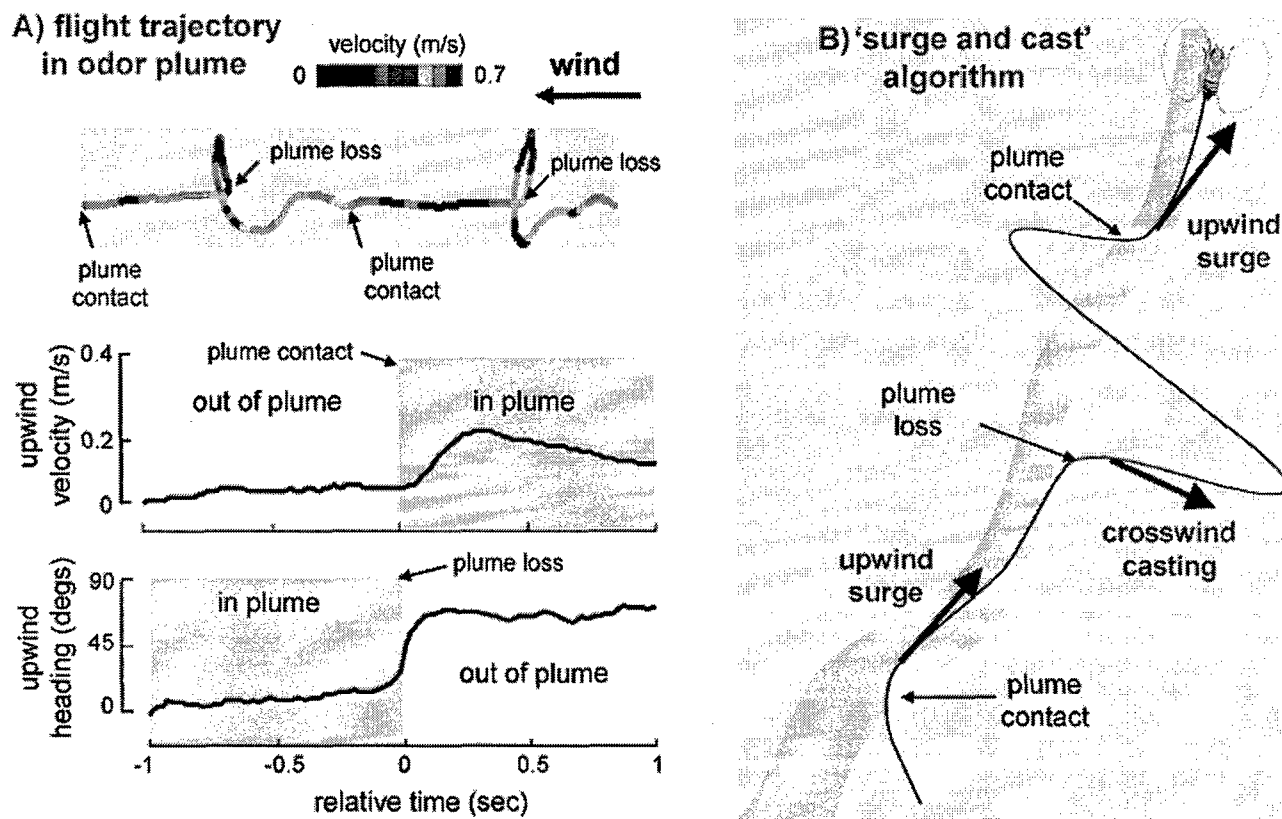
A) flight trajectory in odor plume

velocity (m/s) 0 ▮▮▮▮ 0.7   **wind** ←

plume loss

plume loss

plume contact

plume contact

upwind velocity (m/s)

0.4

plume contact

out of plume   in plume

0.2

0

upwind heading (degs)

90

in plume   plume loss

45

out of plume

0

-1   -0.5   0   0.5   1

relative time (sec)

B) 'surge and cast' algorithm

plume contact

upwind surge

plume loss

crosswind casting

upwind surge

plume contact

Figure 6: 'Surge and cast' algorithm allows fruit flies to localize an odor source by moving upwind in the presence of a odor plume and casting crosswind upon plume loss. A) Experimental data show that velocity increases upon plume contact. Upon plume loss, heading shifts from upwind to crosswind. B) Schematic representation of algorithm.

Conclusions

We have developed an integrated framework for simulating the flight dynamics and control strategies of the fruit fly. By taking a bottom-up approach based on physically and biologically realistic components, we are able to formulate and test explicit hypotheses regarding flight control at levels ranging from stroke-by-stroke stabilization of pitch to long-range flight through a tunnel. Special emphasis is placed on the sensory feedback components of the model, which limit the potential information available to controllers in our model, just as real sensory systems must do in real flies. The availability of the modeling environment enables inquiry and analysis into the principles underlying insect flight control in a closed-loop, feedback driven system. This approach is necessary due to tight coupling between motor output and multi- modal sensory input, making flight control difficult to study with traditional reductionist approaches that elucidate feed-forward mechanisms. By adopting this integrative modeling approach in conjunction with further biological experimentation, we hope we will be able to provide some insight into the nature of the solutions that endow flies with their remarkable flight and goal directed behaviors. Such an endeavor seems worthwhile, because, as anyone who has tried to rid a kitchen of fruit flies knows, these animals are robust performers in a wide range of environments and in the face of severe environmental perturbations.

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14. ABSTRACT

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